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# Dynamic Group Formation With Intelligent Tutor Collaborative Learning: A Novel Approach for Next Generation Collaboration

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**ABSTRACT** Group Formation (GF) strongly influences the collaborative learning process in Computer-Supported Collaborative Learning (CSCL). Various factors affect GF that include personal characteristics, social, cultural, psychological, and cognitive diversity. Although different group formation methods aim to solve the group compatibility problem, an optimal solution for dynamic group formation is still not addressed. In addition, the research lacks to supplement collaborative group formation with a collaborative platform. In this study, the next level of collaboration in CSCL and Intelligent Tutoring System (ITS) platforms is achieved. First, initial groups are formed based on students learning styles, and knowledge level, i.e. for knowledge level, an activity-based dynamic group formation technique is proposed. In this activity, swapping of students takes place on each permutation based on their knowledge level. Second, the formed heterogeneous balanced groups are used to augment the collaborative learning system. For this purpose, a hybrid framework of Intelligent Tutor Collaborative Learning (ITSCL) is used that provides a unique and real-time collaborative learning platform. Third, an experiment is conducted to evaluate the significance of the proposed study. Inferential and descriptive statistics of Paired T-Tests are applied for comprehensive analysis of recorded observations. The statistical results show that the proposed ITSCL framework positively impacts student learning and results in higher learning gains.

**INDEX TERMS** Human-computer interaction, computer-supported collaborative learning, group formation, knowledge level, collaborative learning, intelligent tutoring system.

## I. INTRODUCTION

In today's entrepreneurial and technological digital ecosystem, the term "HomoConnectus" (always wanted to be connected) is widely used to visualise the impact of interactive technologies on human behaviour and creative thinking. This concept encapsulates the idea of interconnected people using a computer as a medium, sharing ideas in open spaces of

interaction, and for co-building new frameworks. Interactive technologies or computer mediation learning environment promotes collaborative creative learning and critical thinking. Collaborative creative learning is a pedagogical technique in which students collaborate to learn and share their knowledge by working on similar learning problems [1]. In a conventional learning environment, collaborative learning (CL) is used for group activities, training, and projects. The important aspects of Computer-Supported Collaborative Learning (CSCL) are group forming, individual's participation, role assignments, and activity orchestration [2].

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Effective Group Formation (GF) is vital to achieve effective collaboration as GF encourages students to mutually discuss and learn from each other [3]. GF divides students into different clusters by assigning them some activities such as assessments and quizzes. Mainly, GF is categorised into homogeneous and heterogeneous groups. In homogeneous groups, all the students are on the same knowledge level and learning abilities, which implies their grades are on par with each other. In contrast, heterogeneous groups have students with different knowledge levels, learning abilities, and personal characteristics [4]. Furthermore, GF is based on attributes such as knowledge level, behaviour, learning styles, interests, random selection, and instructor selection. GF has been a prominent yet challenging topic of research, and the literature lacks consensus among authors on the selection of significant attributes in GF [5].

In this study, we have achieved the balanced heterogeneous groups by creating task-based activities in the form of a short quiz to assess the knowledge level of students. After the permutation of each activity, students are swapped into different groups based on their knowledge levels. Following this method, it is suggested that balanced heterogeneous groups can be established during learning. These balanced groups of students will be more effective in collaborative learning, yielding better performance, i.e., higher learning gain than random students. A number of studies are currently available within a broad domain of GF; however, these studies only focus on GF in a static learning platform and the formation of homogeneous groups. Balanced groups based on student's knowledge and learning abilities are not fully elucidated and require an in-depth analysis. These balanced groups need an intelligent collaborative platform where the students are involved in the collaborative creative learning process. Thus, our study complements GF aspects with the intelligent collaborative learning environment of CSCL and the Intelligent Tutoring System (ITS).

An essential part of the collaborative learning environment is CSCL, which is based on theories of learning and cognition. The authors in [6] highlighted three different learning theories, i.e. socio-constructivist theory, sociocultural theory, and shared cognition theory. These theories are based on the interactions amongst students in peer learning and working on a shared problem in a given environment, towards grasping the critical concepts. One of our recent works [7] exploited Intelligent Tutor-Supported Collaborative Learning (ITSCL), which offered an intelligent technological climate following constructivist theory, sociocultural theory, and shared cognition theory of collaborative learning. Following the similar lines, the current study employs an intelligent collaborative learning environment that is capable to support the aforementioned theories of CSCL.

The proposed study aims to achieve the following twofold contributions. First, a novel activity-based technique for dynamic group formation has been proposed that addresses the GF by swapping students into different groups based on their learning style and knowledge level. Thus, serving

as a foundation for the determination of balanced heterogeneous groups. Secondly, these heterogeneous groups are used to experience the Intelligent Tutor-Supported Collaborative Learning system (e.g., ITSCL). Consequently, balanced heterogeneous groups using ITSCL helps students to achieve the next level of collaboration, which in turn enhances the students' collaborative learning process, leading towards an increase in their learning gains.

The rest of the paper is organised as follows: Section II covers the state of the art providing the motivation for the proposed study. Moreover, Section III presents the methodology adopted to develop the proposed platform. The implementation and experimentation setup are provided in sections IV and V, respectively. The results are then presented and discussed throughout the Section VI. Finally, section VII concludes the paper.

## II. RELATED WORK

The current study spans the two different research dimensions, i.e. Group Formation (GF) in Computer-Supported Collaborative Learning (CSCL) and integration of CSCL with Intelligent Tutoring System (ITS) from an augmented collaborative perspective. From prior research, it is found that GF is the most crucial problem, affecting 'students' collaborative learning outcomes. Several exemplary works have summarised GF attributes and techniques; for example, [8] proposed a GF approach through an evolutionary algorithm. The proposed algorithm compared the evolutionary GF approach with the manual approach used by a teacher with ten years of experience in this domain. These groups are created based on each student's professional, psychological and the level of experience. The obtained results reached 83.46% average similarity that proves the potential of the algorithm. Another study explored the integration of collaborative learning within virtual higher education and proposed a pedagogical model for virtual learning [9]. The study highlights among its conclusions the need for careful planning, an adequate dynamic to form collaborative groups, the relevance of student practices related to everyday use of technologies, the change of the teaching role, and autonomy in the management of learning.

The authors in [10] used personality traits and performance as GF attributes, exploiting the ant-colony optimisation technique. In their study, the authors focused on the student's performance traits and individual performance as key attributes to form different groups for collaborative learning. Another study aimed to improve GF using knowledge and learning style as key attributes and to apply K-means along with Fuzzy clustering techniques [11]. The authors in [8] used inter-homogeneity, intra-heterogeneity, and empathy as a criterion to optimise group formation by an intelligent computational approach. Similarly, authors in [12] propose the use of students' speech during collaborative activities to access group formation. Speech activity can act as a vital indicator for accessing the quality of groups being formed. However, it increases the possibility of an imbalance,

where one participant over-shadows all others, necessitating groups to be re-structured. In their study, authors used two approaches to access performance gain and reported a 36% and 72.8% compared to baseline approaches when used I-Codes-1 and I-Codes-2, respectively. These results are promising in terms of the given environment; however, the authors have not included detailed insight into the speech activity, which undermines the overall performance. The authors have not taken into account aspects such as dialogue-level information, including speaker sequences.

Furthermore, building on the hypothesis that interaction among students is a promising metric for obtaining optimized group, authors in [13] propose a novel Genetic Algorithm-based Group Formation Scheme with Penalty Function (GAGFS-PF). Their proposed approach considers the heterogeneity of students knowledge level and uses it in conjunction with the homogeneous nature of social interactions to generate a collaborative learning group experience with balanced learning characteristics for improved student learning. The proposed approach works well; however, it is built on the assumption that student knowledge level, learning roles, and social interaction among members have the same importance when dealing with group formation. Authors in [14] overcome this deficiency by proposing a new approach based on the genetic algorithm approach for achieving homogeneous groups. In addition, they propose using student personality traits as group creation criteria. These metrics are known to influence students' academic performance greatly and can also be related to their academic success. In this regard, the Big Five Inventory (BFI) metrics are used to evaluate the personality traits. All personality traits are given equal weightage and then accessed. This produces significantly improved results compared to earlier approaches. Still, the lack of granular differentiation among various personality traits in terms of assessment undermines the performance of their approach.

In earlier studies, performance as a key quality attribute was also used by [15] to form dynamic groups for those students who are sometimes misfit in any group and referred to as "orphan students". They used the vickrey auction based and learning-enabled algorithm for GF. This algorithm focused on reducing communication overhead during coalition formation. The authors in [16] used teamwork and learning style as quality attributes for constructing a highly heterogeneous group.

Genetic algorithms have been used for forming optimal collaborative learning groups [17]. A controlled experiment was designed with 238 students, quantifying their personality traits through the "Big Five Inventory" (BFI), forming working groups and developing a collaborative activity in programming and related courses. The experiment results allowed validation, not only from a computational point of view evaluating the algorithm performance but also from a pedagogical point of view, confronting the results obtained by students applying the proposed approach with those obtained through other GF strategies.

Furthermore, learning style, competence, and interactions have been used with particle swarm optimisation techniques for GF in learning environments [18]. This study investigated the use of learning style, student/learner competence, and interactions as primary factors in GF and learning theories and subsequently found that these three attributes play a vital role in dynamic and effective GFs. In another study, learning styles with semantic web techniques and genetic algorithms have also experimented with dynamic group formations [19]. The authors in [20] also proposed a GF mechanism for heterogeneous groups in collaborative learning for non-technical courses of sociology and history.

Considering team roles, another study used the dynamic team as a key attribute to form groups for learning using an evolutionary algorithm [21]. Personality traits play a vital role in the learning process; considering this, another study used unsupervised learning and regression analysis techniques to form learning groups that provide effective learning mechanisms [22]. Knowledge level and compatibility were used to form dynamic groups for learning using a clustering group approach with a genetic algorithm [23]. Some studies also focused on gender as an essential aspect for GF as some authors suggest that gender sometimes affects the learning group performance along with attendance and content [24]. The authors in [25] used knowledge level and learners' interest as key attributes using the particle swarm technique for GF.

Both ITS and CSCL are multidisciplinary areas of cognitive psychiatry, computer science, and educational technologies [7]. Furthermore, ITS and CSCL both are computer-supported technologies that provide pedagogical and cognitive support to the students. Several studies have used CSCL integration; however, most studies provide collaboration between two students, and their collaboration is achieved outside the ITS environment, i.e. through audio/video speech [7]. In addition, such studies primarily provide collaboration for random groups or teacher-decided groups.

To combine collaborative learning with ITS, Cognitive Tutor Authoring Tool (CTAT) was introduced using synchronised tutor engines [26]. CTAT is an authoring system for collaborative learning that dynamically switches between different learning theories according to learners capacity. It selects and presents its learner with such relevant material that is according to their learning ability. The students interact with the updated learning strategies, which are created using the relevant content of the course. Another study proposed a system on students' collaboration utilising their personal computers to work on a shared problem [27]. Students communicate through an audio chat enabled with a collaborative/shared opinion option(s) on a specific problem. However, the groups of students are decided by teachers, and no such option of dynamic group formation is provided based on any key attribute. Similarly, another system was proposed by [28] to support collaborative learning for elementary level students using the ITS system. The proposed system explored joint

collaborative and individual learning strengths, exploring the benefits of binary learning methods instead of a single one. The authors proposed teacher-decided pairs for collaborative learning through ITS by using a shared problem view so that the students could see each other's actions [29]. Moreover, a different study by the same authors proposed the Collab-ChiQat system to use the pair programming technique for solving linked list problems with random group selection [30]. The authors in [31] proposed a combination of novice and expert pair programmers with ITS by using random group selection.

The aforementioned studies successfully extended ITS for collaborative learning; however, there are some limitations for adaptive and collaborative learning. First, these are only used for a mathematical fraction or pair programming in which collaboration is limited to only two students in each group and does not support more students. Second, most of the studies used student communication with another student through Skype/audio, recorded outside the ITS environment. This interaction is not captured and analysed by ITS. Third and most importantly, no prior GF of the students was formulated without the intervention of instructors, i.e. 'teacher deciding groups'.

On the contrary, our proposed method, i.e. ITSCL, tackles all these limitations and provides a collaborative platform for a group of students with an interactive learning environment. Moreover, the collaborative groups are formed by dynamic swapping using the proposed algorithm within the ITSCL model. To the best of our knowledge, no prior study uses effective GF with CSCL and ITS integration.

### III. METHODOLOGY

Our methodology focuses on the GF aspect of CSCL by proposing a dynamic group formation approach provided in section III (A). The resulting heterogeneous balanced groups are then used to enhance the application of ITSCL, which is presented in section III (B).

#### A. GROUP FORMATION IN CSCL

In CSCL, GF is based on personal, social & cultural characteristics, group selection (i.e., self-selection, instructor-led selection), psychological and cognitive diversity. The students' characteristics, such as knowledge level and learning style, are the core elements to achieve a balanced group of students. Based on students' knowledge level and learning style, we propose a novel methodology, where students' initial clusters are formed, as shown in Figure 1. Details regarding each intermediary step is further explained in subsequent sections.

##### 1) INITIAL GROUP FORMATION

###### a: IDENTIFYING LEARNING STYLES (ILS)

Learning style has been used as an influencing attribute in GF. To identify the learning style of students, learning behaviour is usually analysed in four dimensions: (1) processing

(reflective or active), (2) perception (sensitive or intuitive), (3) receiving or verbal and (4) understanding (global or sequential) [32]. To identify the Index of Learning Style (ILS), previous studies have used the M. Felder learning style model that contains 44 questions [33]. The ILS questionnaire can be brought down to twenty questions; five questions for each dimension of learning behaviour that enable students to be organised in groups with similar learning styles. In our study, we have used the following attributes, following Felder's learning styles model: 1) visual, 2) verbal, 3) sensory, 4) intuitive, 5) active, 6) reflective, 7) global, and 8) sequential [34].

###### b: CALCULATING KNOWLEDGE LEVEL

The knowledge level is regarded as the most relevant attribute to form educational groups because of its effects on the group outcomes, as seen in the previous studies [35], [36]. To determine the knowledge level of students, short quizzes are set up [37]. In our study, we created eight quizzes to be taken by the students, which in turn helped with the formation of initial students' clusters.

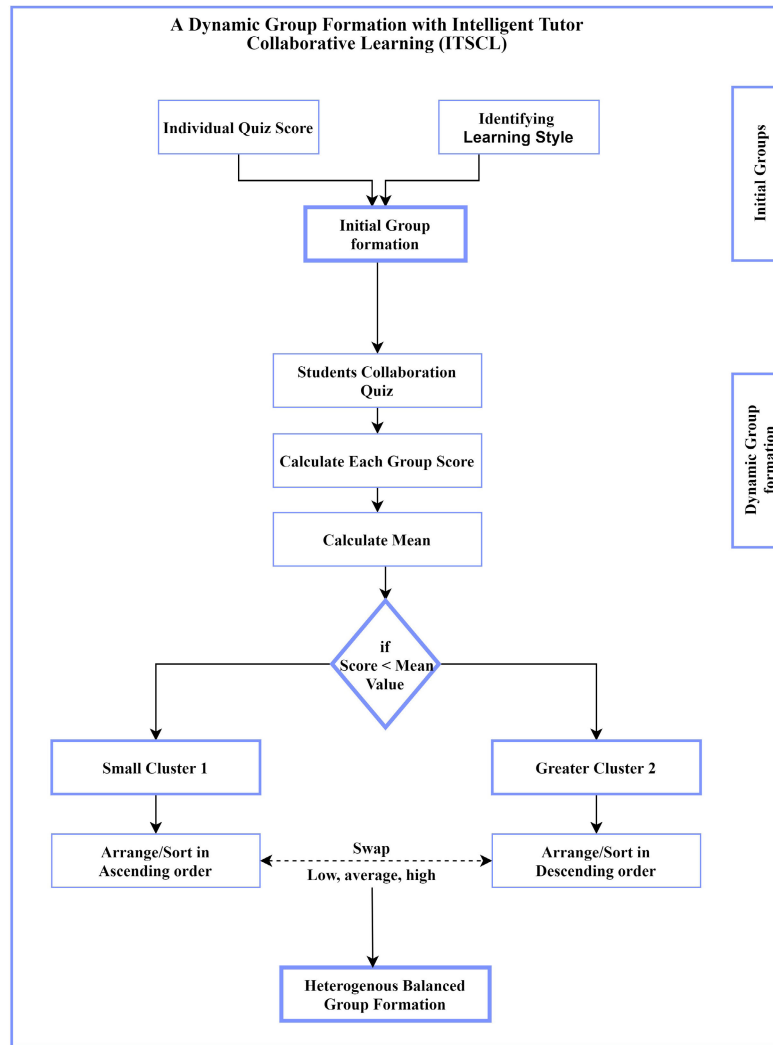
##### 2) DYNAMIC GROUP FORMATION

Following the creation of initial clusters, activities are designed on which dynamic swapping of students takes place. For designating an activity, we created a quiz of five questions. Each student individually solves the activity with an option to collaborate with peers using a chat. Students can chat with each other to build consensus on the common answer and submit a collective answer. Researchers often use the chat in a collaborative learning environment, which implies that the integration of chat is more productive and provides a richer collaborative learning environment [38].

In our study, we assigned activities to different student groups; after each permutation of the activity, the knowledge level of each group of students and the mean value of the score is calculated. The proposed methodology compares the score of each individual with the mean value. If the score is equal to or higher than the mean value, the student is assigned to the greater cluster and vice versa. This results in an array of two clusters; i.e., smaller cluster array and a greater cluster array. The smaller cluster array is sorted in ascending order, and the greater cluster array is sorted in descending order. These two sorted arrays are then swapped to get a balanced group of students, i.e., each group will have low, average and high mark students. We performed these activities before swapping the students, resulting in heterogeneous balanced groups of students.

#### B. COLLABORATIVE LEARNING

Interactive technologies impact human behaviour and creative thinking [37]. There is a need to encapsulate the idea of interconnected people using a computer as mediation, sharing ideas in open spaces of interaction, and co-building new ideas. When students work collaboratively, they can influence each other's thought processes, ask questions, articulate



**FIGURE 1.** Proposed GF methodology.

their reasoning and misconceptions, and reflect upon their knowledge.

Our study provides a deeper understanding of how system information can influence and interact with students' collaborations and how the balanced group formation aspect of CSCL can play a vital role in enhancing collaborative learning. It is important to note that focusing on one aspect, i.e. group formation of CSCL, is not enough; therefore, our study achieves the next level of collaboration by creating balanced groups, which augments the collaborative learning environment.

#### 1) ITSCL COLLABORATIVE PLATFORM

The Intelligent Tutoring Supported Collaborative Learning (ITSCL) platform supports both individual and collaborative learning [7]. In individual learning, a single student interacts with ITSCL, which uses the same tutoring process as traditional ITS. In addition, a student can interact with

ITSCL from his personal computer, and ITSCL provides the pedagogical model of instruction. Whereas in collaborative learning, a small group of students is involved in the learning process. The process is as such that first, a student responds to the problem individually. Then, the answers are shared with peers, following the social constructivist view of CSCL. Thus, the students have the provision to seek help and guidance and can reflect upon their knowledge.

Furthermore, ITSCL enables students to share their gained knowledge and reflect on peer answers via comments/instructions. Commenting on peer responses enables students to share their knowledge, ask questions, clear misconceptions, and articulate their reasoning that influences each other's thought processes. Besides, students can rate peer answers, as rating peer answers in collaborative learning could be a method for fostering collaboration and providing encouraging results [38]. This sharing knowledge and rating procedure can lead to high collaboration and



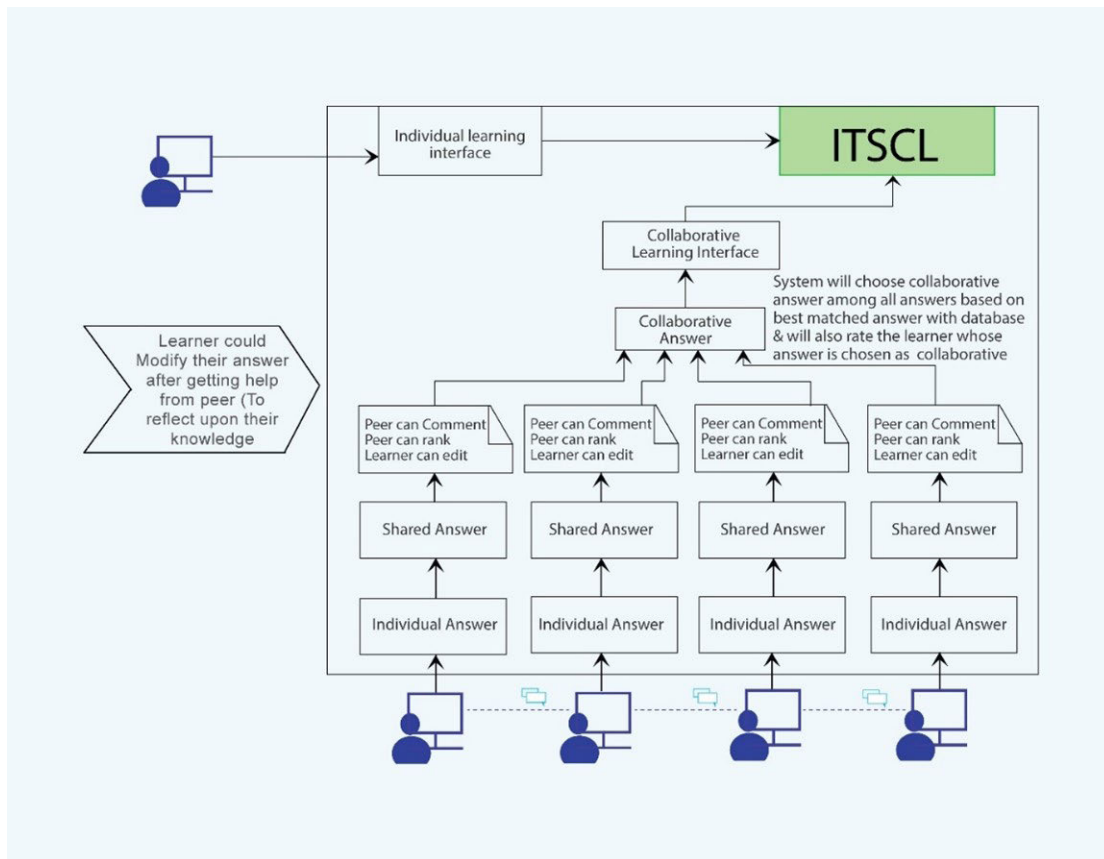


FIGURE 2. ITSCL framework [7].

shared understanding, where students can reflect upon their knowledge, review their responses, and modify/update their answers. After concluding their responses, ITSCL analyses each student's response and selects a more authentic/matched answer as the collaborative answer. This learning procedure helps student's individual as well as collective responsibility in a collaborative group. ITSCL collaborative mode of learning is presented in Figure 2.

#### IV. IMPLEMENTATION

The proposed system provides a web-based interface to students for interaction. The system design is based on the ComBAT (Component-Based Authoring Tool) technology, where each component acts as a software object that interacts with other components. The component-based architecture allows each component to provide an interface that conforms to a prescribed behaviour while encapsulating certain functionalities. As a result, multiple components work independently and mutually provide adaptive tutoring services.

##### A. DYNAMIC GROUP FORMATION

Dynamic group formation activity consists of the following steps:

##### 1) INITIAL GROUP FORMATION

As explained in section III-A(1), the initial GF is based on identifying learning style and individual quiz scoring. Students learning styles are identified by Felder *et al.* [34], and the initial knowledge level is calculated from the quiz, which each student individually solved. The initial individual quiz consists of Multiple Choice Questions (MCQs), as shown in Figure 3.

##### 2) DYNAMIC GROUP FORMATION

Activities are designed to create initial groups based on learning styles and individual learning scores. Six activities are created, each with six MCQ's. A sample quiz is shown in Figure 4. This activity is different from the initial individual activity; students can now chat with peers to build consensus on the common answer and submit a collective response.

##### B. STUDENTS INTERACTION WITH ITSCL

The students then interact with the ITSCL. ITSCL provides single tutoring in a natural language interface using a dialogue-based mechanism of NDLtutor (Negotiation Driven Learning). NDL using ITS provides an intuitive, natural language paradigm for interaction between students and the system [39], [40].

**ITSCL Individual Student Quiz**

Welcome Student

**MENU**

**Basic OOP Concepts**

- One of the basic concepts in Object Oriented Programming approach is bundling both data and functions into one unit known as \_\_\_\_\_.
  - ☐ Simple Variable
  - ☒ Object
  - ☐ Bundle
- In the switch case statement, every case should have a \_\_\_\_\_ statement as the last statement.
  - ☐ Jump
  - ☒ Break
  - ☐ Exit
- Classes provide users with a method to create \_\_\_\_\_ data types.
  - ☐ character
  - ☐ Primitive
  - ☒ User-defined

**FIGURE 3.** Quiz for calculating individual knowledge level.

**ITSCL Collaborative Quiz**

Welcome Student(s)

**MENU**

**Basic Programming Concepts**

- \_\_\_\_\_ is automatically created when constructors are used.
  - ☐ Objects
  - ☒ Destructors
  - ☐ Arrays
- What does your class can hold?
  - ☐ Data
  - ☒ Functions
  - ☐ Both A & B
- >> is called as \_\_\_\_\_ Operator.
  - ☐ Insertion
  - ☒ Extraction
  - ☐ Greater than
- While overloading binary operators using member function, it requires argument/s.
  - ☐ Zero
  - ☒ One
  - ☐ Two

**Submit**

**Chat with Colleagues to Provide a Collective Answer**

Student 1: for Q1 answer correct option is B

Student 4: no sorry I think C is correct

Student 5: yes B is correct

Student 2: Ok can you explain why B is correct?

Comment:

**Submit**

**FIGURE 4.** Quiz for calculating collaborative knowledge level.

It is worth mentioning that the ITSCL interface offers two different learning interfaces, i.e. individual and collaborative learning interfaces.

#### 1) ITSCL INDIVIDUAL LEARNING

When students navigate to the individual learning interface, ITSCL provides instruction to the individual student. The student interacts with ITSCL through a natural language

interface, as shown in Figure 5. ITSCL instructs and facilitates students to construct their knowledge.

#### 2) ITSCL COLLABORATIVE LEARNING

ITSCL provides a collaborative learning paradigm using two-level of interactions. In the first interaction, a group of students interacts with ITSCL. ITSCL posts a question to a group of students who have shared the same problem

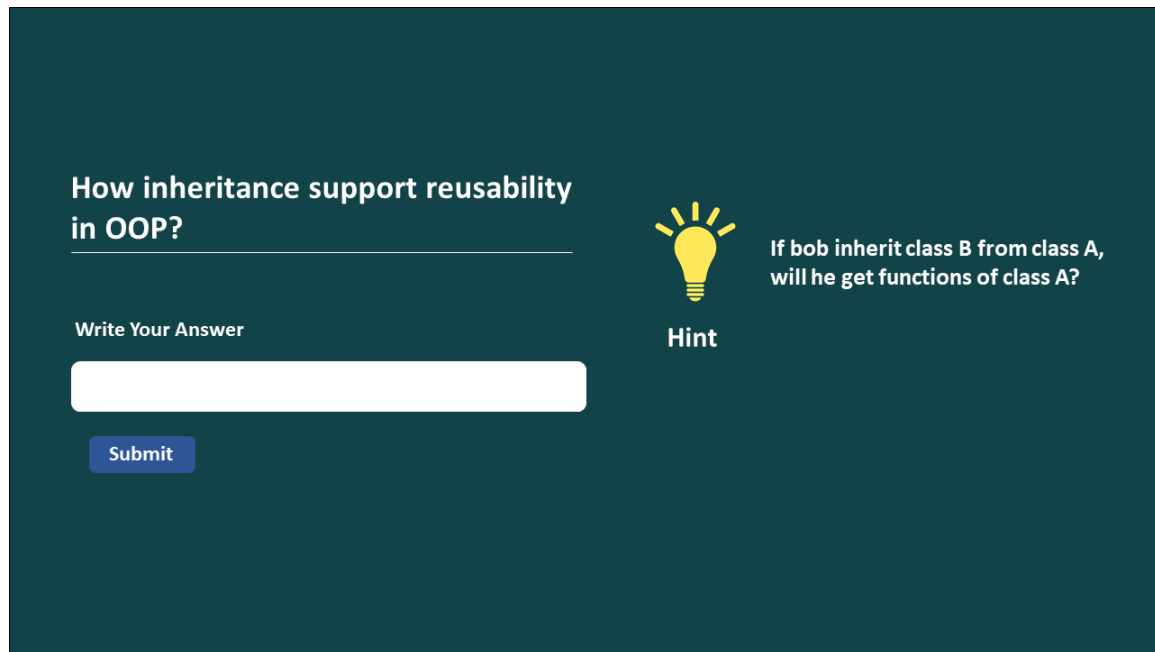


FIGURE 5. ITSCL individual learning interface.

view. These groups of students collaborate by commenting and rating the answers. The second level of interaction is student-student interaction. Students can also directly seek help from peer students through chat. The collaborative learning view is shown in the Figure. 6.

## V. EXPERIMENTAL SETUP

We conducted this experiment with 20 students from the Bachelor of Computer Science cohort of the 4<sup>th</sup> semester at a reputable university. Out of the total participants, 55% participants were male and 45% were female students. The average age of the participants was 21 years and they belonged to the same ethnic background. As the research was carried out in the pandemic (November 2020 – March 2021), having consistent participants was challenging due to the changing lockdown and social distancing restrictions/guidelines. Therefore to have reliable results we have only considered 20 students who were consistent throughout this period.

This experiment targeted the “object-oriented programming” module because the students were familiar with the module and the programming paradigms from the first semester. They also had experience using online learning environments such as Moodle; however, none participants had previous experience or ideas about intelligent tutoring systems. Before the session, participants were oriented on using the ITSCL and the different options available to them about the usage

### A. GROUP FORMATION

#### 1) GENERATING INITIAL CLUSTERS

According to our proposed methodology, initial clusters are formed by determining learning style and calculating

knowledge level. Learning style is determined from the Felder’s questionnaire [34] presented in Table 1, and knowledge level is calculated from individual quiz activity, as illustrated in Table 2.

It is important to note that the Felder learning style questionnaire consists of different parameters to judge/count learner’s knowledge levels. Where, 0 represents nil/absence of a parameter in a student, while 1 represents satisfactory performance as per parameters. Felder algorithm parameters are:

- Sensory: Students with sensitive learning styles are thinking concrete, practical and factual.
- Intuitive: are concerned about the theories and concepts.
- Visual: Learners remember best when they see something in the form of images/videos.
- Verbal: Learners get more out of words—written and spoken explanations.
- Active: Learners are more comfortable in classroom activities and group work.
- Reflective: The learner’s tendency is toward individual learning.
- Global: learners tend to learn in large jumps, absorbing material almost randomly without seeing connections and then suddenly “getting it.”
- Sequential: learners tend to gain understanding in linear steps, with each step following logically from the previous one.

#### 2) DYNAMIC GROUP FORMATION

##### a: STUDENTS SWAPPING

As discussed in section IV, students are given activities to solve and are used to calculate their knowledge.



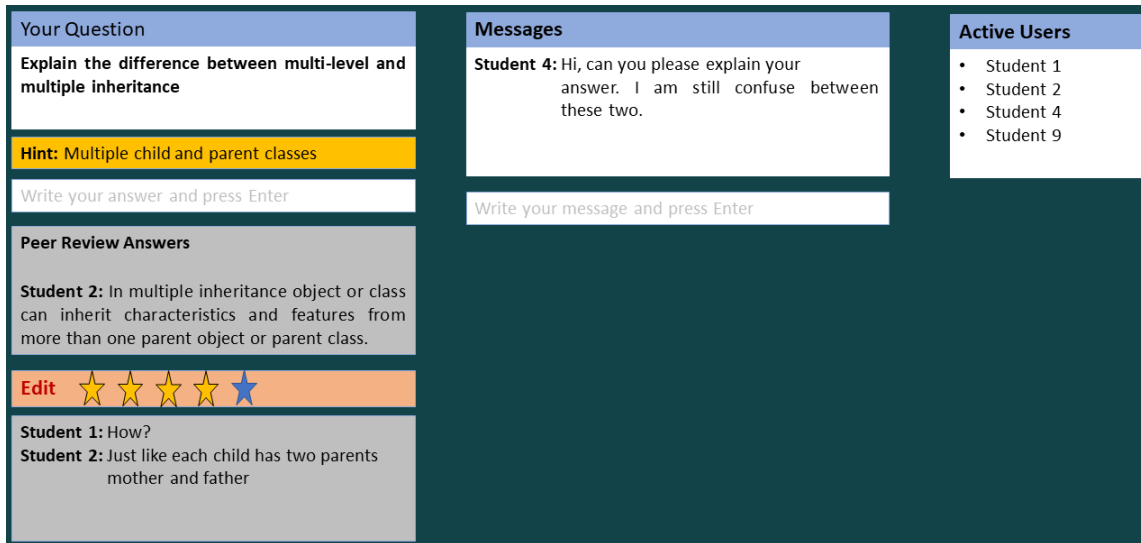


FIGURE 6. ITSCL collaborative learning interface.

TABLE 1. Calculated learning styles.

Sr. No	Sensory	Intuitive	Visual	Verbal	Active	Reflective	Global	Sequential
Student 1	0	1	1	0	0	1	0	1
Student 2	0	1	1	0	0	1	0	1
Student 3	1	0	1	0	1	0	1	0
Student 4	0	1	1	0	1	0	0	1
Student 5	1	0	1	0	0	1	0	1
Student 6	1	0	1	0	0	1	0	1
Student 7	0	1	1	0	0	1	0	1
Student 8	0	1	0	1	0	1	1	0
Student 9	0	1	1	0	1	0	0	1
Student 10	1	0	1	0	0	1	0	1
Student 11	1	0	1	0	0	1	0	1
Student 12	0	1	1	0	1	0	0	1
Student 13	0	1	0	1	0	1	1	0
Student 14	0	1	1	0	0	1	1	0
Student 15	0	1	1	0	0	1	1	0
Student 16	0	1	0	1	0	1	1	0
Student 17	1	0	1	0	1	0	0	1
Student 18	1	0	1	0	1	0	0	1
Student 19	0	1	1	0	0	1	0	0
Student 20	1	0	1	0	1	0	0	0

Students solve these activities individually (as shown in Figure 3) as well as collaboratively (as shown in Figure 4). Individual marks are used for student swapping, and collaborative group marks are used to evaluate the group's overall performance.

The study followed the algorithm proposed by [41] to swap students based on the mean value of the group. The algorithm calculates each student's points and calculates their mean or average value. Students are then divided into two clusters called greater point groups and smaller point groups. The threshold of this division is the mean value, i.e. if the group points are greater than the mean/ average value, they are placed into the greater point cluster and vice versa. The greater point cluster is sorted in descending order, and the smaller point group is sorted in ascending order. Afterwards,

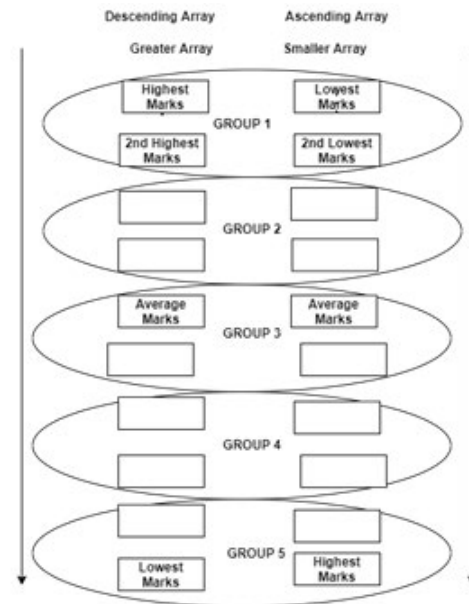
we created two arrays named "toBeSwappedFrom" and "toBeSwappedTo" in order to swap students of each group. The algorithm's pseudo-code is shown in Algorithm 1.

The students from the two sorted arrays were grouped into five different groups. Students groups are formed from the greater array and smaller arrays, as shown in Figure 7. The swapping process continues after each group activity. We observe that after each activity, the swapping of students decreases as the students cannot be swapped to their initial groups; that is when the activities are stopped. Group formation after the first, second, third, fourth, fifth, and sixth activities can be found in Figures 8-13.

In the GF Figures (i.e., Figures 8-13), it can be observed that little swapping took place as activities increase. For instance, in the fifth activity (i.e. second last), only two groups

**TABLE 2.** Calculated knowledge levels.

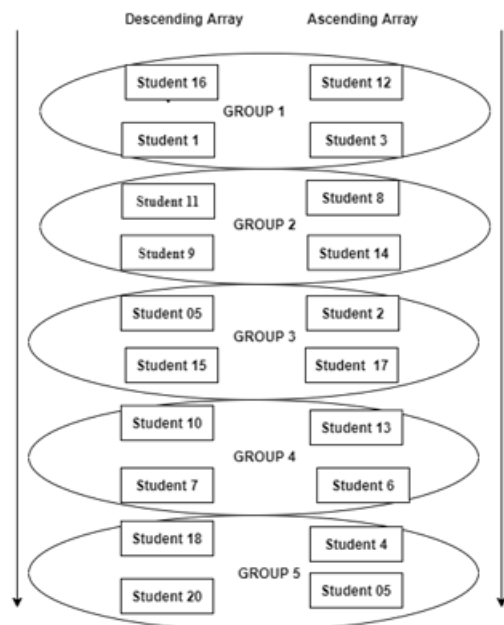
Students	Knowledge level
Student 1	71%
Student 2	71%
Student 3	100%
Student 4	57%
Student 5	85%
Student 6	75%
Student 7	95%
Student 8	57%
Student 9	72%
Student 10	71%
Student 11	100%
Student 12	80%
Student 13	64%
Student 14	98%
Student 15	100%
Student 16	84%
Student 17	100%
Student 18	92%
Student 19	57%
Student 20	65%

**FIGURE 7.** Group formation from Greater and Smaller arrays.**Algorithm 1** Student Dynamic Swapping Algorithm [41]

```

groupPoint ← getGroupPoints()
mean ← calculateMean(groupPoint)
greaterGroupPoint[]
smallerGroupPoint[]
for groupPoint do
    if groupPoint → point < mean then
        smallerGroupPoint ← groupPoint
    else
        greaterGroupPoint ← groupPoint
    end if
end for
smallerSorted ← AscendingSort(smallerGroupPoint)
largerSorted ← DescendingSort(greaterGroupPoint)
toBeSwappedFrom[]
while smallerSorted do
    smallStudent ← smallerSorted[i] → getStudents()
    smallStudent ← DescendingSort()
    for smallStudent do
        toBeSwappedFrom ← smallStudent
    end for
end while
toBeSwappedTo
while largerSorted do
    largeStudent ← largerSorted[i] → getStudents()
    largeStudent ← AscendingSort()
    for largeStudent do
        toBeSwappedTo ← largeStudent
    end for
end while

```

**FIGURE 8.** Group formation after the first activity.

### B. STUDENT'S INTERACTION WITH ITSCL

There were three interactions of students with ITSCL. First, students interacted with ITS individually. Second, random groups of students interacted with ITSCL. Third, a group of students arranged by the proposed algorithm involved in the learning process with ITSCL.

#### 1) INDIVIDUAL LEARNING

In the first interaction, students learned about Object-oriented programming concepts individually with ITSCL. Each student interacted with ITS individually. Twenty students were involved in the individual learning process with ITSCL.

were swapped. Furthermore, in the last group formation for activity six, no swapping took place.

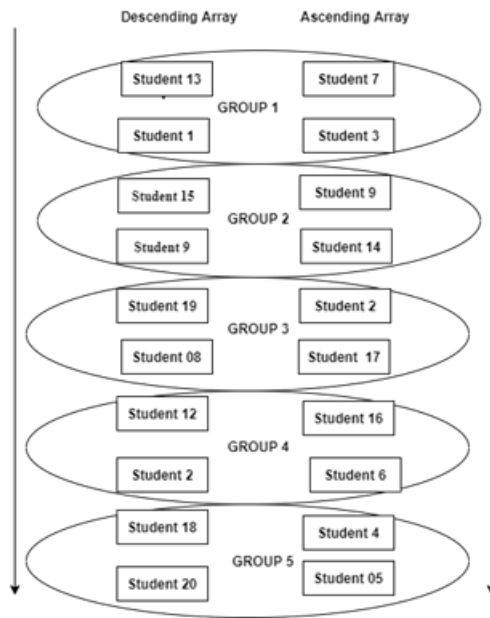


FIGURE 9. Group formation after the second activity.

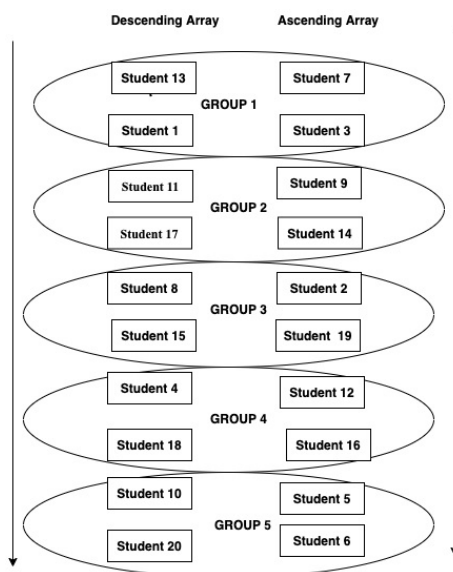


FIGURE 10. Group formation after the third activity.

## 2) RANDOM COLLABORATIVE GROUPS

In the second interaction, random student groups were involved in learning with ITSCL. Twenty students were divided into five groups, each group consisting of 4 students. Here, the group formation was random.

## 3) PROPOSED 'METHODOLOGY'S COLLABORATIVE GROUPS

According to the proposed methodology, twenty students were divided into five clusters; each cluster consisted of four students. Each activity was a quiz that contained five questions with four options given; among them, only one answer was the correct answer. One point was awarded for each correct answer.

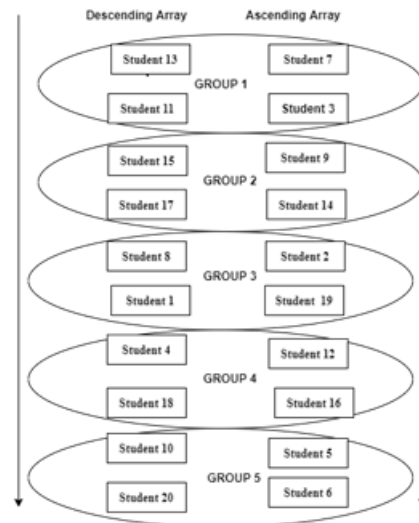


FIGURE 11. Group formation after the fourth activity.

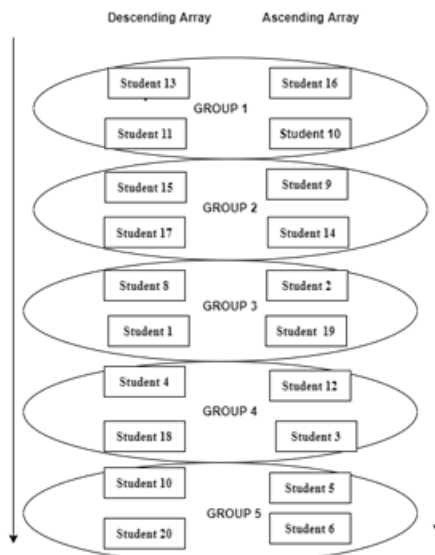


FIGURE 12. Group formation after the fifth activity.

This study aims to validate the efficiency of the proposed technique of dynamic group formation. In this research, we tried to assess the influence of collaborative balance groups on the learning process in CSCL. The verification of the learning gain of the proposed study is based on the statistical comparison. Validating through statistical comparison shows the difference between the following conditions:

- Finding learning gain of individual students.
- Finding learning gain of randomly collaborative students.
- Finding learning gain of proposed methodology collaborative groups.
- Statistically comparing results of individual learning gain with randomly collaborative learning groups.
- Statistically comparing results of randomly collaborative learning groups with groups generated by the proposed methodology.

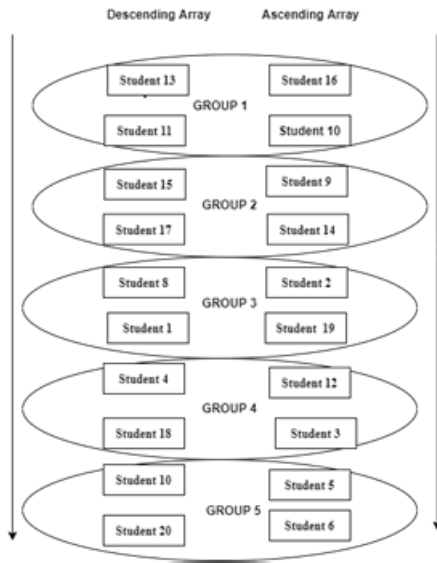


FIGURE 13. Group formation after the sixth activity.

- Statistically comparing results of randomly collaborative learning groups with individual and groups generated by the proposed methodology.

## VI. RESULTS AND DISCUSSIONS

We performed statistical analysis by performing paired T-Test. Paired T-Tests is a statistical measurement that compares the means of two measurements from the same samples. This test is also called the dependent T-Test, paired T-Test and repeated measure T-Test. This technique is commonly used to find statistical differences between two conditions, e.g. Pre-Test and Post-Test. Moreover, this technique is validated to check the hypothesis, e.g. any difference between the Pre-Test and Post-Test. The Pre-Test and Post-Test data are compared and analysed using Statistical Package for the Social Sciences (SPSS v25) by running paired T-Test. SPSS is a set of software programs used for batched and non-batched statistical data analysis [42]. The reason behind using SPSS is its user-friendly interface to perform statistical analysis with ease and can create the basic visualisation.

### A. PAIRED T-TEST RESULTS

To calculate results of individual, random collaborative groups and groups achieved through the proposed methodology, Paired T-Test was applied on Pre and Post-Test.

P-value or probability value graph is used to visualise the statistical significance of the findings. P-value graph tests the validity of the null hypothesis. In our results, P valued graph shows significant results, as shown in Figure 14. If t-values lie in the red region, then the null hypothesis is rejected and vice versa.

Performing paired T-Test, the researcher must keep a confidence level  $\alpha$  of how likely the null project is rejected, so we retained a 95% confidence level given by equation 1.

However, there is some area that is critical between the rejection areas and fail to rejection and could be found by equation 2.

$$\text{Confidence level}(\alpha) = 0.95 \quad (1)$$

$$\text{Degree of freedom}(df) = n - 1 \quad (2)$$



FIGURE 14. P-valued graph.

First, for individual learning condition, Paired T-Test was applied, having 19 degrees of freedom and  $t(20) = 3.263$ , there was much difference in the Pre-Test (2.90) and Post-Test (4.15), as shown in Figure 15. Also, the significant level ( $p=0.004$ ) is less than the threshold (0.05). The paired test was also performed on learning gains and its measurements are: mean (1.70), standard deviation (1.081) and highly significant ( $p<0.05$ ). The overall Paired T-Test result is given in Table 3.

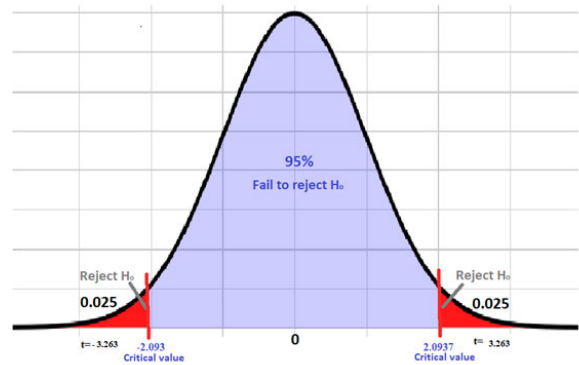


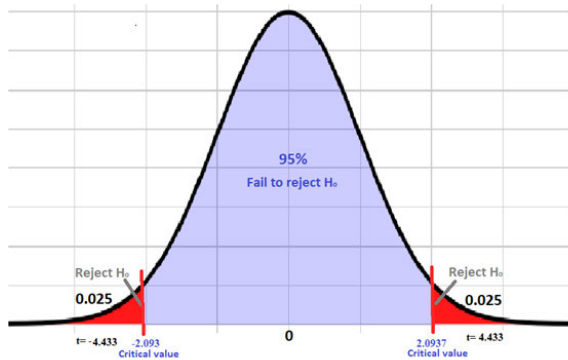
FIGURE 15. P-value Paired Test Graph for Individual Condition.

Secondly, for the collaborative learning condition, Paired T-Test was applied, having 19 degrees of freedom and  $t(20) = 4.433$ ; there was much difference in the Pre-Test (3.85) and Post-Test (5.75), as shown in Figure 16. Also, the significant level ( $p=0.000282$ ) is less than the threshold (0.05). The paired test was also performed on learning gains and its measurements are: mean (2.40), standard deviation (1.081), and highly significant ( $p<0.05$ ).

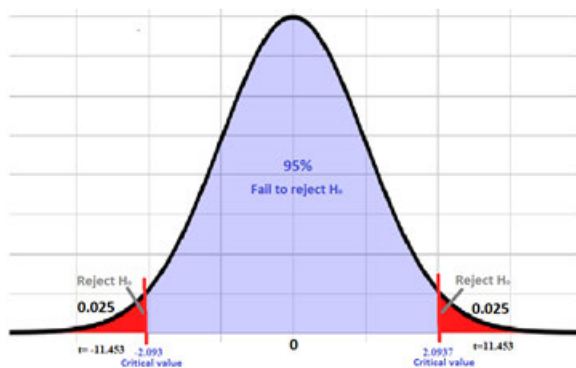
Thirdly, in collaborative groups of the proposed methodology, Paired T-Test was applied, having 19 degrees of freedom

**TABLE 3.** Paired T-Test Results.

Conditions	No. of Students	Pre-Test		Post-Test		Gain	
		Mean ( $\mu$ )	SD ( $\sigma$ )	Mean ( $\mu$ )	SD ( $\sigma$ )	Mean ( $\mu$ )	SD ( $\sigma$ )
Individual	20	2.90	2.049	4.15	1.387	1.70	1.081
Random Collaborative groups	20	3.85	1.386	5.75	1.551	2.40	1.27
Collaborative groups generated by methodology	20	3.70	1.301	6.75	1.208	3.10	1.165

**FIGURE 16.** P-value Paired Test Graph for random Collaborative groups.

and  $t(20) = 11.453$ ; there was a significant difference in the Pre-Test (3.70) and Post-Test (6.75), as shown in Figure 17. Also, the significant level ( $p=0.0001$ ) is less than the threshold (0.05). The paired test was also performed on learning gains and its measurements are: mean (3.10), standard deviation (1.165), and highly significant ( $p<0.05$ ).

**FIGURE 17.** P-value Paired Test Graph for Proposed Collaborative groups.

Comparing these three modes of learning, i.e. individual, random collaborative, and proposed collaborative groups, the results of paired T-Test show a significant difference. Students performed better in the Post-Test in all three conditions. The rejection of the null hypothesis of proposed collaborative groups is greater than random groups, and the random group has greater than individual learning. In Post-Test, Students perform better in random collaborative (mean 5.75) than the individual (mean 4.15) and proposed collaborative groups (6.75) than random groups (mean 5.75). Also, analysing learning gain across three conditions, proposed collaborative have high performance than both random and individual and

random perform better than individual condition. The overall comparison of the three conditions is given in Table 3.

## B. DESCRIPTIVE STATISTICS OF FREQUENCY ANALYSIS

Descriptive statistics of frequency analysis of learning gains for the following three different conditions are measured. The statistical analysis used the following data (samples):

- The descriptive analysis of individual work.
- The descriptive analysis of randomly generated groups.
- The descriptive analysis of groups generated by the methodology.

This analysis (also shown in Figure 18) clearly shows better results in collaborative conditions than the individual. The results show that three students got zero marks in individual, one in the random grouping, and zero in proposed groups. This frequency analysis graph shows improvement in learning gain in the proposed collaborative conditions. We observed that random groups produced higher learning gains than individual conditions. Furthermore, students have achieved high learning in the proposed 'methodology' than random and individual groups.

The proposed approach was also compared with relevant literature from the years 2012 to 2021. These research articles were shortlisted based on their relevance to the problem and their measurement metrics, such as Post-Test mean and Study Mean increase (percentage). In the past, authors have used multiple different approaches such as inter-homogeneous and intra-heterogeneous genetic GF [43], student compatibility based GF [44], student demographic-specific GF [45], student personality-based genetic GF [46], student preference-based cooperative learning GF [47] and student ethnicity-based cooperative learning GF [48]. Despite this wide variety of approaches, these aforementioned studies do not consider individual learning styles for GF. In order to overcome this, the proposed work uses individual knowledge

**TABLE 4.** Comparative analysis of results.

Technique	Post-Test Mean	Study Mean Increase (percentage)
Genetic algorithm [43]	4.53	-
Justice-based linear model [44]	-	2.65
Exact Algorithm [45]	0.7	-
Group formation in ITS [46]	3.50	-
Cooperative Learning [47]	3.47	-
Mathematical learning gains [48]	5.28	-
<b>Our Proposed Methodology</b>	<b>6.75</b>	<b>3.05</b>



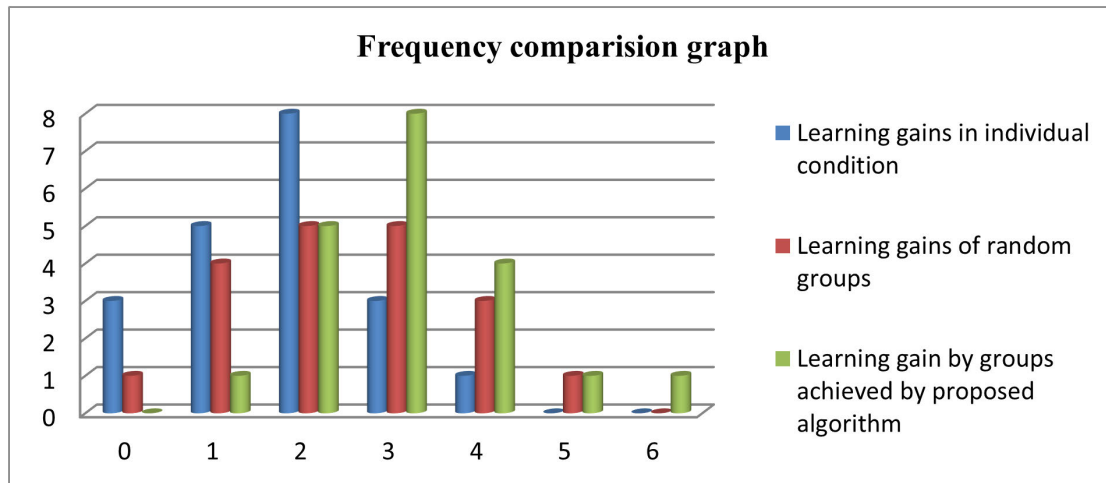


FIGURE 18. Comparative analysis of Learning gains.

gain and learning style to ensure efficient results, which outperforms existing literature. As a result, the proposed approach reports an increased Post-Test Mean of 6.75 and Study Mean Increase (percentage) of 3.05, as illustrated in Table 4.

## VII. CONCLUSION

In this paper, the authors have proposed a novel methodology for dynamic group formation based on the students' learning styles and knowledge levels. In contrast to the existing group formation techniques, the proposed method allows dynamic swapping of students on activity assignments. After each activity, students are swapped into their relative clusters on their knowledge level. We supplement the resulting groups with the collaborative learning environment of ITSCL, which provides effective communication and collaboration. ITSCL was also used as a tool for experimentation and evaluation.

The experimentation results report that the dynamic GF of the proposed method achieves higher collaboration gain compared to random groups. In addition, statistical analysis using Paired T-Tests and frequency comparison shows that balanced groups increase students' learning gains. Furthermore, the achieved heterogeneous balanced groups indicate better results when compared to random and individual learning.

The importance and demand for e-learning platforms have significantly increased due to the COVID-19 pandemic. AI-based platforms like an intelligent tutoring system replace the traditional static collaborative learning approaches by replicating a human tutor and supporting the learning theory. Moreover, it eliminates human intervention by automated group formation using knowledge level as well as automated swapping using the proposed algorithm. Nevertheless, ITS with different learning strategies and scaffolding techniques can be beneficial for students to learn and engage in a stress-free environment.

## VIII. LIMITATIONS AND FUTURE WORK

This study provides a promising direction for exploring dynamic group formation in collaborative Intelligent Tutoring Systems (ITSs) and achieved significant results compared to the existing solutions. However, this study only focused on a single module, i.e., "Object-Oriented Programming", and investigated with Computer Science undergraduate students. The algorithm's effectiveness in terms of dynamic group formation can be assessed with different modules and groups of students. It will also be interesting to measure the algorithm's performance with different levels of students, i.e., seniors vs juniors and students with different demographics. Furthermore, the research was carried out during the COVID-19 pandemic, limiting us to using physical resources, which would have been readily available in normal times. Another limitation of the study is that we primarily focused on knowledge level that is more related to the cognitive nature than the social collaboration of student's nature.

Intelligent tutoring systems collaborative learning (ITSCL) have significantly improved learning platforms accommodating more students in the learning process and content delivery however, ITSCL adaptation and acceptability at the massive scale still requires significant improvement in collaborative learning and effective groups formation for effective learning.

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